



Research article

Technology adoption and capacity planning under technological evolution and demand uncertainty

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Abstract: Hi-tech industries have experienced rapid evolution in manufacturing technology, leading to current technology (i.e., the technology currently employed in the firm's production process) becoming obsolete more quickly. Furthermore, fluctuating demand also harms the firm's expected profit due to the costs of shortages or excess demand. In this circumstance, the firm must allocate appropriate resource capacity to hedge the risks associated with the above uncertainties. In this study, we proposed a technology adoption and capacity planning model that accounted for demand uncertainty and technological evolution. It also considered the economic life of the current technology and the corresponding capacity and resource allocation plan. The research problem was modeled by stochastic dynamic programming (SDP). Each corresponding action presented a possible economic life of the current technology. The reward of an action was the risk-adjusted expected profit of the corresponding capacity planning problem, modeled as a stochastic mixed-integer programming (SMIP). For the solution approach, the SMIP sub-problems were solved by a parallel sampling-based differential evolution (PSDE) procedure with an infeasible-solution repair mechanism, and the SDP model was then solved by backward induction. The numerical results showed that technology and demand uncertainties jointly affect expected profit and technology adoption decisions. A higher probability of new technology introduction raises the expected profit and the cost of delaying replacement, whereas greater demand uncertainty reduces profitability. The optimal policy retains the current technology for a short period and then re-evaluates the decision; the current technology is retained until the end of the planning horizon only when the decision maker's risk aversion exceeds a threshold, which is lower under high demand variability and under a low probability of new technology introduction. Moreover, the proposed PSDE efficiently solves the stochastic optimization problems and scales well to larger problem instances.

Keywords: capacity planning; stochastic dynamic programming; technology adoption; demand uncertainty; technological evolution

Mathematics Subject Classification: 90B30, 90C15, 90C39, 90C59

1. Introduction

In recent decades, high-tech manufacturing industries have experienced rapid technological development. For example, Intel has launched new microarchitectures every year since 2010. The feature size reduced from 32 nm (Westmere) in 2010 to 14 nm (Coffee Lake) in 2017, and it was projected to reach 10 nm (Cannonlake) in 2018. Display technology has undergone rapid change. A series of display technologies, including OLED (organic light-emitting diode), flexible OLED, QLED (quantum dot light-emitting diode), and AMOLED (active-matrix organic light-emitting diode), were introduced over the last decade. Shortly thereafter, the display panels were projected to be lighter, larger, thinner, more colorful, cost-effective, flexible, and less power-consuming [1].

The current technology may become obsolete soon due to technological innovations. Therefore, if the technology replacement is postponed, the firm may stay behind its competitors. In contrast, an immediate replacement may result in a payback burden. This is because changes in the product technology will replace the currently used manufacturing equipment with new ones. This action is very costly because the investment in high-tech manufacturing resources requires substantial capital [2–4]. In this circumstance, the firm faces a dilemma: either keep the current manufacturing equipment or replace it with new equipment.

Further, the demands of high-tech products also vary over time. An excess of capacity will cause a massive loss for a firm due to inventory costs and the discounting of outdated products. On the other hand, if the capacity is lower than demand, shortage costs will occur. In this situation, the firm must decide on an appropriate resource and production quantity level to minimize these costs. Considering demand uncertainty makes the capacity planning problem more robust, and decision-makers must account for and address demand variability [5].

Given the above observations, technology adoption and capacity planning are highly coupled: a slight change in one will affect the other, and vice versa. Therefore, a minor improvement in decision quality will yield significant savings. To address such problems, stochastic programming and optimization offer an effective modeling tool for decision-making under uncertainty [6–8].

In this study, we propose a model that simultaneously addresses two decisions. The first is the technology adoption policy, formulated as a stochastic dynamic programming (SDP) model in which each action corresponds to the number of periods during which the current technology is retained, and new technologies are introduced sequentially according to a Markov process. The second is the capacity planning and resource allocation problem associated with each action, formulated as a stochastic mixed-integer programming (SMIP) model under i.i.d. demand. The SMIP sub-problems are solved by a parallel sampling-based differential evolution (PSDE) procedure, and the SDP model is then solved by backward induction.

The contributions of this study are twofold. First, the two decisions are optimized jointly rather than sequentially: The risk-adjusted value of the capacity plan obtained from each SMIP model serves as the reward of the corresponding adoption action, so that the economic life of the current technology reflects technological evolution and demand uncertainty. Second, a solution procedure tailored to the

structure of the integrated problem is developed. The problem is shown to decompose into independent SMIP sub-problems and an SDP recursion, and the computationally demanding sub-problems are solved by PSDE, which evaluates the demand scenarios in parallel and uses a problem-specific repair mechanism to guarantee feasible solutions.

The rest of this paper is organized as follows: The literature review is presented in Section 2. The mathematical model is developed in Section 3. In Section 4, a solution method is proposed. Comprehensive experiments and validations are provided in Section 5. Finally, conclusions and remarks are discussed in Section 6.

2. Related works

2.1. Approaches to technology adoption

Due to the rapid pace of technological innovation, new technologies are introduced more frequently. They cause invested technologies to become obsolete more quickly, and the firm faces a payback burden on its resource investment. Consequently, a decision regarding technology adoption significantly affects the firm's long-term business performance and has been an interesting research topic in operations management [9,10].

Early approaches primarily focused on the physical deterioration of the assets in use. Bellman [11] first introduced a dynamic programming solution for asset replacement problems in which asset age defined the system states. Derman [12] observed specific maintenance or replacement decisions in which the states of machines and their transition probabilities were considered. Hatoyama [13] extended Derman [12] by considering uncertainty in maintenance actions and in part inventories. Wagner [14] developed an equipment replacement model in which system states were defined as the number of periods in the planning horizon that an asset is kept.

Several researchers have addressed the replacement problem by focusing on technological innovations. These researchers assumed that technological improvements were introduced deterministically, in terms of timing or of productivity, cost, and revenue [15,16]. However, these assumptions cannot account for the difficulty of forecasting technological innovations with specific information.

The above limitations were tackled in later studies. A Markovian process was utilized to model technological obsolescence [9,17,18]. Additionally, Cho et al. [19] developed a combination of the Delphi forecasting technique and the semi-Markov concept. Hartman and Rogers [20] proposed an economic life (EL) model that imposes a lower computational load than previous work by eliminating economically inferior alternatives during processing. However, these approaches assumed that only one technological improvement could be introduced in each period; thus, they failed to account for the possibility of multiple innovations entering the market simultaneously.

In most of the above-mentioned studies, the technology adoption problem was modeled by SDP, which estimated the reward of each possible action. However, a minor inaccuracy in reward estimation may lead to a significant revenue loss and an incorrect decision on technology adoption for the following reasons: First, manufacturing resources in high-tech industries are capital-intensive. For instance, in the semiconductor manufacturing industry, over 60% of the total cost is for equipment acquisition alone [3]. Second, demand for hi-tech products occurs stochastically; thus, demand fluctuations can cause shortages or excess costs. Therefore, it is crucial to incorporate the technology

adoption problem into the capacity planning and resource allocation problem to hedge the risks associated with technology and demand uncertainties.

2.2. Approaches to strategic capacity planning and resource allocation

Decisions concerning capacity planning and resource allocation have attracted considerable attention from researchers in operations management [21–24]. Wang et al. [25] stated that capacity planning and resource allocation are highly coupled. Thus, it significantly affects the firm's long-term profit. Wang and Hou [26] addressed the joint capacity expansion and allocation problem in the semiconductor testing industry, considering different resources and a finite budget, under the assumption of fixed demand. Later, demand uncertainty was addressed by Wang et al. [5], Geng et al. [27], and Wang and Wang [3].

Developments have sought to unify perspectives on technology adoption and capacity investment, introducing stochastic and dynamic frameworks that capture the interaction between technological progress and operational decision-making. In the last decade, research on technology adoption and capacity investment under uncertainty has advanced considerably, moving beyond static frameworks toward dynamic and stochastic representations. For instance, Balter et al. [28] analyzed capacity investment and the timing of technology adoption under demand uncertainty using a real-options approach, while Sendstad et al. [29] investigated how firms' risk preferences influence optimal adoption and capacity investment in emerging technologies. Ye et al. [30] further explored strategic innovation and technology adoption behavior in competitive markets where the performance and timing of new technologies are uncertain. These studies provide valuable insights into how technological uncertainty, competition, and risk aversion shape adoption behavior.

In parallel, several researchers have extended the modeling of capacity investment under uncertainty. Filomena et al. [31] introduced a joint framework for technology selection and capacity investment under stochastic demand and cost parameters, highlighting the interaction between technology choice and capacity sizing. Correia and Melo [32] developed a multi-period stochastic programming model that integrates facility location and capacity expansion under demand uncertainty, while Jiang and Fan [33] examined how process efficiency and flexibility affect investment decisions in volatile markets. These studies demonstrate the evolution of capacity investment research toward richer representations of uncertainty, flexibility, and technological change.

Despite these advances, the literature has not integrated new technology adoption and capacity planning under uncertainty in technological innovations and demand. Most existing models treat technology adoption as a one-time or static decision, without modeling the stochastic evolution and replacement of technologies over time, and they often separate strategic investment from operational capacity allocation and resource-planning layers. As a result, the dynamic interaction between long-term technology evolution and short-term operational performance remains underexplored. By combining a Markovian process of technological evolution with an SMIP model for operational capacity planning, our study establishes a unified framework that explicitly links strategic technology replacement and operational capacity allocation under uncertainty. This integration highlights the importance of jointly analyzing technological evolution and operational decision-making, thereby offering a framework that extends the understanding of capacity investment and new technology adoption decisions under uncertainty.

2.3. Solution approaches

Regarding the solution approach, linear programming and mixed-integer programming are used as exact methods to address material planning and capacity allocation problems [34–36]. However, the problem size in real-world industries has increased significantly; as a result, these methods are often time-consuming and may fail to solve large-scale problems. To address such issues, soft-computing approaches supported by high-performance computers have rapidly become widespread. Bard et al. [37] applied a simulated annealing method to solve a capacity expansion in the semiconductor manufacturing industry. Wang and Chen [38] proposed an ant algorithm to solve capacity planning and resource allocation in a decentralized supply chain. Ip et al. [39], Wang et al. [25], Wang et al. [40], and Chen et al. [4] addressed a set of aspects of capacity planning by using a genetic algorithm (GA).

Another competitive method is the differential evolution (DE) algorithm [41]. Mohajery and Khoshalhan [42] employed the DE algorithm to solve a single-item resource-constrained aggregate production planning problem. Lieckens and Vandaele [43] used the DE algorithm to solve the lot-sizing problem in stochastic supply chain management systems. DE shows its excellent performance potential compared to others. Tušar and Filipič [44] showed that DE explores the decision space more efficiently than GA does in numerical multiobjective optimization. Further, Deb et al. [45] conducted a performance comparison of DE, GA, and Particle Swarm Optimization (PSO) in antenna design. The study concluded that the number of generations required for convergence in DE is the least among GA and PSO.

Although technology replacement and resource planning are closely coupled, few researchers address them simultaneously. Therefore, a generalized model is needed to precisely resolve the problems. Regarding solution approaches for MIP problems, DE appears to be a leading candidate among metaheuristic methods. Motivated by the above observations, we develop a capacity planning model incorporating technology replacement decisions under demand and technology uncertainties.

3. Problem formulation

In this study, we focus on capacity planning and resource allocation, incorporating technology adoption under technology and demand uncertainties. The first uncertainty is the possibility of introducing a new technology into the market. It is assumed that new technologies are under development and might be successfully introduced into the market with some probability. The second uncertainty is the uncertainty in product demand. A decision-supported model is developed here to decide (i) the economic life (EL) of the technology currently employed in the firm's production process (called current technology) and (ii) the corresponding resource and capacity allocation plan to meet the customer's demands. The former decision, i.e., the EL model, is formulated as an SDP model, while the latter is formulated as a stochastic mixed-integer programming (SMIP) model. Our objective is to maximize the risk-adjusted expected profit over the planning horizon. The mathematical model is described as follows:

3.1. Economic life model of technology

Several assumptions of the EL model are explained as follows:

- (1) The planning horizon is finite.

(2) New technologies are introduced to the market in the form of new types of machines that provide the same functionality while offering higher unit profit and throughput compared to machines of the existing technology.

(3) New technologies will be introduced sequentially, and their innovations will be inherited from the previous technologies. Therefore, the technology roadmap, timing, and magnitude of the technological innovations can be projected.

(4) The unit profit of products produced by a specific technology decreases over time because of the competition from new technologies.

(5) Due to the capital intensity of resource investment, the information involved in acquisition, operation, maintenance costs, and salvage values will be investigated and given in advance.

The following notation is used in the model:

Indices for the EL model

- i technology type ($i = 1, \dots, I$). $i = 1$ is the current technology in the initial period;
- j index of available technologies can be replaced with the current technology ($j = 2, \dots, I$ and $j \neq i$);
- t period of time ($t = 0, 1, \dots, T$). $t = 0$ is the initial period;
- α discount factor ($0 \leq \alpha \leq 1$).

Components of the EL model

Stage: Each stage is a period of time t .

State: The system state is defined as i , which implies that technology i has been used to manufacture the firm's products.

Action: A possible action at the state i in period t is defined as n . This implies that the firm will retain technology i for another n period(s) from period t . For example, in Figure 1, if the firm is staying in state 1 in period 0, given the maximum planning period is 3 ($T=3$), the number of available actions at state 1 is $3 - 0 = 3$. This implies that the firm can keep the current technology for 1, 2, or 3 periods, from period 0.

Reward: The reward of an action n at state i in period t is defined as $P_{n,i,t}$, which is the risk-adjusted expected profit obtained by solving the capacity planning and resource allocation problem (called a sub-problem) associated with this action n .

Technology uncertainty: $p_{i,j}^{(t,n)}$ denotes the probability that the new technology j is introduced into the market in period $t+n$, given that technology i was in use in period t . Assume that new forms of the current technology are introduced in sequence, and follow the Markov chain with the transition matrix $Pr_t = [p_{i,j}^{(t,n)}]$. Note that Pr_t is an upper triangular matrix since technological progress is irreversible, so transitions from a newer technology to an older one are not allowed. The evolution of display technologies provides an illustrative example of such sequential technological progress.

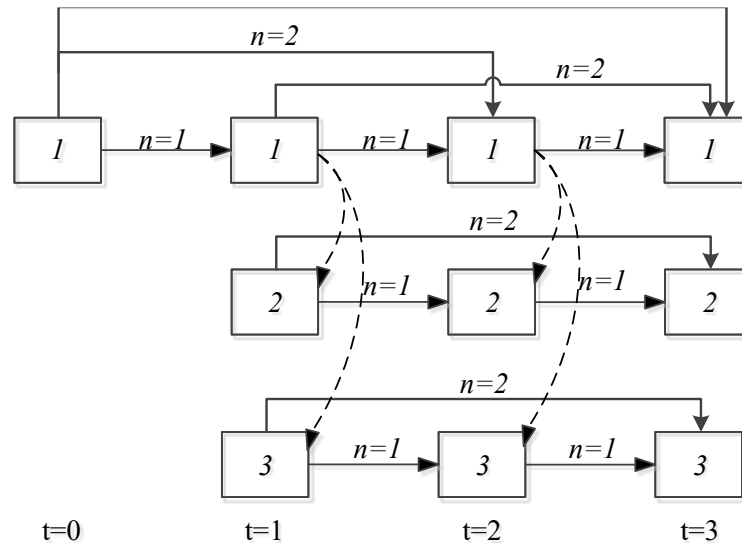


Figure 1. The EL model of new technology adoption.

The optimality equation is written as follows:

$$G_{i,t} = \max_{n: n \leq T-t} \left\{ \alpha^t P_{n,i,t} + \left[p_{i,i}^{(t,n)} G_{i,t+n} + \sum_{j=i+1}^I p_{i,j}^{(t,n)} G_{j,t+n} \right] \right\}, \quad \forall i, t \quad (1)$$

where

α^t discounted factor of the capital at the end of period t , where $\alpha = \frac{1}{(1+\text{interest rate})}$.

$G_{i,t}$ optimal risk-adjusted profit from the state i in time t through time T . The boundary condition is $G_{i,T} = 0$.

The backward induction equation (1) computes the discounted profit corresponding to each action $n = 1, 2, \dots, (T - t)$, incorporating the probabilistic profit-to-go function $G_{j,t+n}$. The first term from the left-hand side, $\alpha^t P_{n,i,t}$, is the reward of action n discounted to period 0. The second and third terms represent the optimal expected profit from $t + n$ to T . The second term implies that no new technologies will be introduced, whereas the third term implies the introduction of new technologies. After n periods, assuming the current technology is maintained, we assume that all on-hand manufacturing equipment associated with this technology will be sold. The decision to adopt a new technology is determined by the expected profit based on the system state at that time. Previously used technologies are not considered for subsequent replacement decisions.

In the EL model, there are T periods of time and I number of technologies need to be evaluated, which corresponds to $I(T + 1)$ states. Given each state, the average number of actions is $\frac{T}{2}$. Note that

only one initial state is considered in the initial period. Therefore, there are a total of $I(1 + T) \frac{T}{2} - T(I - 1)$ number of actions that need to be evaluated.

Let $f(I, T)$ The number of actions in the EL model is given below.

$$f(I, T) = I(1 + T)\frac{T}{2} - T(I - 1) = \frac{1}{2}IT^2 - \frac{1}{2}IT + T \quad (2)$$

As I and T approach infinity, the term IT^2 dominates Eq. (2). Therefore, the growth rate of the number of actions in the EL model can be characterized by $O(IT^2)$, indicating that the computational complexity grows quadratically with the planning horizon and linearly with the number of technologies. This defines the growing function of $O(IT^2)$.

3.2. Capacity planning and resource allocation model

Recall that the reward of each action in the EL model, called sub-problems, presents a capacity planning problem. Due to product demand variability, the decision-maker needs to determine the production quantity to maximize profit under uncertain demand. Then, the level of resources (machines) is simultaneously determined accordingly. We employ the SMIP model developed by Wang et al. [5] with some modifications. Our objective is to maximize the risk-adjusted expected profit. The following are the model's assumptions:

- (1) Demands of different product types are independent; each is *i.i.d* and given.
- (2) The unit profit of products is decreased over time due to innovative obsolescence, which is assumed to be known.
- (3) The make-to-order (MTO) manufacturing strategy is applied because the life cycle of high-tech products is short, and the inventory can cause a massive loss of revenue.
- (4) Shortage is acceptable, but the firm has to pay a penalty per unit for not satisfying customers' demands.
- (5) The procurement cost of machines is known, and the resource procurement takes place only at the beginning of the economic life.
- (6) There is a second-hand market for unused machines, and their salvage values can be estimated.

The sample average approximation (SAA) method, proposed by Shapiro and Homem-de-Mello [46] and Santos et al. [47], is employed to deal with the SMIP problem. The objective function is formally presented as follows:

$$\text{Max: } (1 - \lambda) \sum_{\delta} \left(\frac{\theta^{\delta}}{\eta} \right) - \lambda \left(\frac{\sum_{\delta} |\theta^{\delta} - \overline{\theta^{\delta}}|}{\eta} \right) \quad (3)$$

where $\lambda \in [0,1]$ is the risk factor, and η is the batch size. $\lambda = 1$ implies the highest risk, and $\lambda = 0$ implies risk neutrality. θ^{δ} is the profit associated with the demand scenario δ . $\overline{\theta^{\delta}} = \sum_{\delta} \left(\frac{\theta^{\delta}}{\eta} \right)$ is the expected profit of the batch, and $\left(\frac{\sum_{\delta} |\theta^{\delta} - \overline{\theta^{\delta}}|}{\eta} \right)$ is the mean absolute deviation (MAD) of the expected profit. Parameter λ is a preference parameter that expresses the decision maker's attitude toward profit dispersion. Since the expected profit and the MAD are measured in the same monetary unit, the ratio $\lambda/(1 - \lambda)$ can be interpreted as the expected profit that the decision maker is willing to forgo to reduce the MAD by one unit; therefore, λ can be determined by asking management how much expected profit they would be willing to give up for a specific reduction in profit dispersion.

A value of $\lambda = 0$ suits a firm that can absorb profit fluctuations, a positive value is appropriate when the irreversible equipment investment is large relative to the firm's financial capacity, and $\lambda = 0.5$, which gives equal weights to the two terms, is used as the reference level in this study. Values close to 1 ignore the profit level and are of limited practical relevance. Notations and mathematical constraints of the SMIP model are described as follows:

Index

- τ index of the planning period associated with the action n . Given each action, $\tau = t + 1, t + 2, \dots, t + n$.
 ρ index of product types ($\rho = 1, 2, \dots$).

Parameters

- $b_{i,\rho,\tau}$ unit profit of a product type ρ produced by technology i in period τ .
 c_i unit cost of purchasing a machine of technology i .
 $d_{\rho,\tau}^\delta$ market demand for product type ρ in period τ in scenario δ .
 e_i unit renting cost of the machine of the technology type i .
 o_i unit salvage value of selling out a machine of technology i .
 $r_{i,\rho}$ throughput of product type ρ produced by machines of technology i .
 s_ρ unit shortage cost of the product type ρ .
 w_i working hours per period of a machine of technology type i .
 $y_{i,\rho}$ target utilization of the machine of the technology type i producing product type ρ .

Decision variables

- F_τ^δ profit gained in the period τ in scenario δ .
 $K_{i,\tau}^\delta$ number of on-hand machines of technology type i in period τ in scenario δ .
 $Q_{i,\tau}^\delta$ number of rented machines of technology type i , at a period τ in scenario δ .
 $S_{\rho,\tau}^\delta$ shortage quantity of product type ρ in scenario δ .
 $V_{\rho,\tau}^\delta$ shortage cost of product type ρ in scenario δ .
 $X_{i,\rho,\tau}^\delta$ number of product types ρ produced in a period τ in scenario δ .

Constraints of the SMIP model:

Required number of machines in each period:

$$K_{i,\tau}^\delta + Q_{i,\tau}^\delta \geq \sum_{\rho} \frac{X_{i,\rho,\tau}^\delta}{r_{i,\rho} w_{i,\rho} y_{i,\rho}} \quad \forall i, \tau \quad (4)$$

Shortage quantity:

$$S_{\rho,\tau}^\delta = d_{\rho,\tau}^\delta - X_{i,\rho,\tau}^\delta \quad \forall i, \rho, \tau, \delta \quad (5)$$

Cost of the shortage quantity:

$$V_{\rho,\tau}^\delta = s_p S_{\rho,\tau}^\delta \quad \forall \rho, \tau, \delta \quad (6)$$

Production quantity constraint:

$$X_{i,\rho,\tau}^\delta \leq d_{\rho,\tau}^\delta \quad \forall i, \rho, \tau, \delta \quad (7)$$

Capital balance constraint:

$$F_{\tau}^\delta = \alpha^{-1} F_{\tau-1}^\delta + \sum_{\rho} b_{i,\rho,\tau} X_{i,\rho,\tau}^\delta - e_i Q_{i,\tau}^\delta - \sum_p V_{\rho,\tau}^\delta \quad \forall i, \tau, \delta \quad (8)$$

Profits of a demand scenario:

$$\theta^\delta = \alpha^n (F_{\tau=t+n}^\delta + o_i K_{i,\tau}^\delta) - c_i (K_{i,\tau}^\delta - k_{i,o}) \quad \forall i, n, \delta \quad (9)$$

Constraint (4) considers the required number of machines in each period, where the number of available machines, owned plus rented, must be at least the number of machines required by the production plan. Constraints (5) and (6) represent the calculation of the shortage quantity and its costs, respectively. Constraint (7) specifies the upper bound on capacity under the MTO manufacturing strategy. Constraint (8) is the capital balance constraint. It is computed by adding the remaining budget, the income from selling products, and subtracting the outsourcing cost and the shortage cost. Constraint (9) depicts the profit of a demand scenario. It is computed by adding the profit obtained after n periods keeping technology i and the salvage value obtained by selling all on-hand machines, minus the procurement cost of machines.

The integration of the EL and SMIP models plays an important role in linking strategic technology adoption decisions with operational capacity and resource planning. The EL model provides a strategic perspective by determining the optimal economic life of the current technology, while the SMIP model captures operational decisions regarding capacity planning and resource allocation under stochastic demand. Accounting for demand uncertainty is essential because the profitability of retaining or replacing the current technology depends strongly on future demand conditions. By using the expected profit obtained from each SMIP solution as the reward in the EL model, the proposed framework establishes a dynamic link between long-term technology adoption decisions and short-term capacity and resource planning.

4. Proposed solution method

Recall that the proposed model combines the EL model under technology uncertainty and the SMIP model under demand uncertainty. The solving procedure will begin by solving the SMIP sub-problems to find the best-found reward for each action. Then, Eq. (1) is applied to determine the most profitable technology adoption policy and the corresponding capacity plan. Because of their computational burden, the SMIP sub-problems are solved by the proposed PSDE procedure tailored to the structure of the problem: it combines the SAA scheme and the standard DE algorithm with a problem-specific repair mechanism for infeasible solutions and the parallel evaluation of demand scenarios. The remainder of this section discusses the PSDE in detail.

4.1. DE algorithm

Soft-computing methods, supported by high-performance computers, have emerged rapidly. Moreover, DE is a simple and powerful algorithm that outperforms genetic algorithms (GAs) in many numerical single-objective and multi-objective optimization problems [44,48]. DE is also employed to solve capacity planning-related problems efficiently [42,43].

The DE algorithm is illustrated in Figure 2. Initially, an initial population of solution vectors is generated. Each vector is called a target vector and represents a solution candidate. The first step is mutation, in which target vectors are randomly selected to generate mutant vectors. Then, the crossover operator is used to diversify the mutant population by exchanging components between the target and mutant vectors. After that, new vectors, named trial vectors, are produced; if infeasible trial vectors are detected, they will be sent to the repair mechanism. Afterward, all feasible solution vectors are evaluated and selected. This process repeats until termination conditions are satisfied. The mathematical expressions of each step are referenced in Price et al. [48].

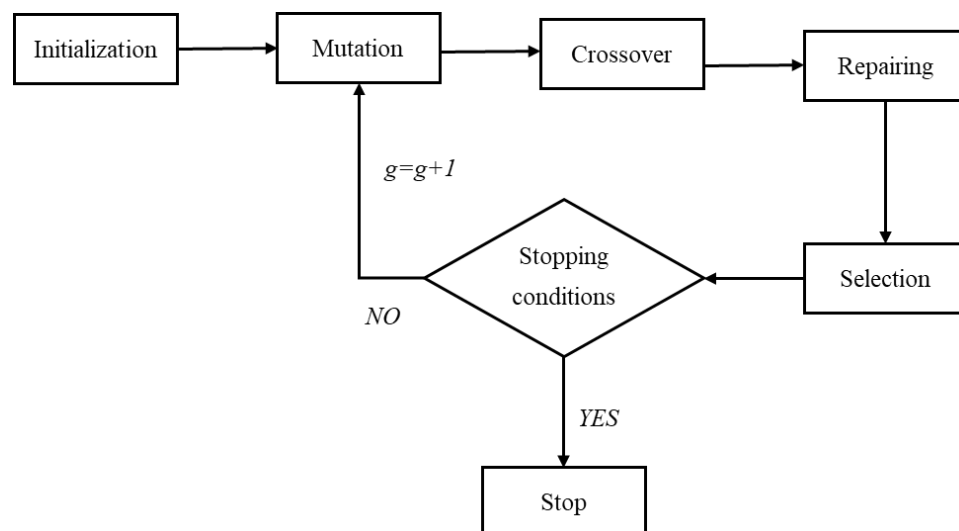


Figure 2. General DE algorithm procedure.

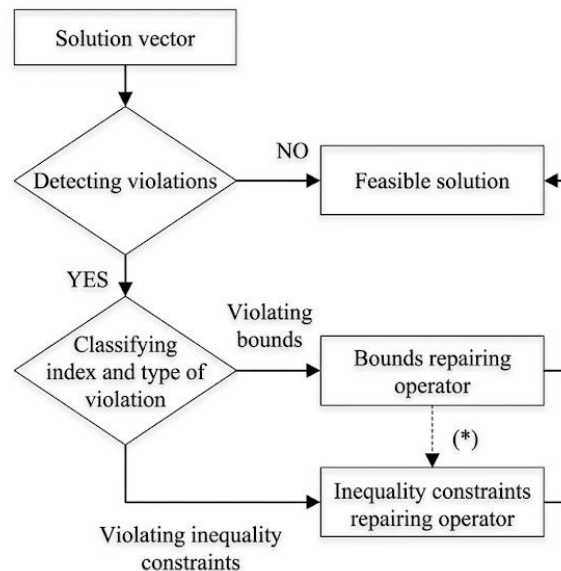
Each solution vector is composed of three types of decision variables in order: number of machines purchased ($K_{i,\tau}^\delta$), number of machines rented ($Q_{i,\tau}^\delta$), and quantity of each product type

produced ($X_{i,\rho,\tau}^\delta$). The objective function of the DE algorithm is Eq. (9), and it is constrained by Eq. (4–8).

4.2. Solution-repairing mechanism

The repair mechanism for infeasible solutions is shown in Figure 3. The first step is to detect the indices of the violated elements in the solution vector and the type of violation it suffered, i.e., a bounds violation or an inequality constraint violation. Second, the infeasible solution is sent to (i) the bounds repairing operator or (ii) the inequality constraints repairing operator accordingly. However, if both types of constraints are violated, the infeasible solution is sent to operator (i) and operator (ii) in order. The DE operators act on real-valued vectors; $K_{i,\tau}^\delta$ and $X_{i,\rho,\tau}^\delta$ are rounded to the nearest integer when a vector is decoded, before the repair of Eq. (10) and the fitness evaluation, and $Q_{i,\tau}^\delta$ is integer since Eq. (10) uses the ceiling operator. The former repair operator replaces the violated elements of the infeasible solution with new values within the lower and upper bounds. In the latter repairing operator, the values of the decision variable type $X_{i,\rho,\tau}^\delta$ and $K_{i,\tau}^\delta$ (i.e., production quantity and required number of on-hand machines) in the infeasible solution vector are kept unchanged, whereas the value of the decision variable type $Q_{i,\tau}^\delta$ is adjusted according to the type of decision variables $X_{i,\rho,\tau}^\delta$ and $K_{i,\tau}^\delta$, which are described mathematically in Eq. (10).

$$Q_{i,\tau}^\delta = \left\lceil \sum_{\rho} \frac{X_{i,\rho,\tau}^\delta}{r_{i,\rho} w_{i,\rho} y_{i,\rho}} - K_{i,\tau}^\delta \right\rceil, \quad \left(\sum_{\rho} \frac{X_{i,\rho,\tau}^\delta}{r_{i,\rho} w_{i,\rho} y_{i,\rho}} - K_{i,\tau}^\delta \right) > 0, \forall i, \tau \quad (10)$$



(*) Both types of violations happen

Figure 3. Operation of the repairing mechanism for infeasible solutions.

4.3. PSDE procedure

The SAA method is employed to solve the stochastic programming problem. The SAA scheme generates M discrete batches of demand realizations, each of size N . Given each batch, we need to solve η discrete MIP problems. This task is usually executed on a single processor, which places a high computational load on the system. Therefore, a parallel computing mechanism is developed in this study. The mechanism first divides η discrete MIP problems into small groups based on the number of processors available on the on-hand computers. Then, small groups are assigned to different processors for simultaneous execution. The procedure of the proposed PSDE is described in Figure 4.

After obtaining the best-found expected profit for each SMIP sub-problem corresponding to each action n , these results are incorporated into the reward function $P_{n,i,t}$ of the EL model. The backward induction (Eq. 1) is then applied to compute the discounted profit-to-go values across all states and actions. Through this process, the EL problem is solved iteratively using profit information from the stochastic capacity planning subproblems, ensuring that technology adoption decisions are consistent with the stochastic demand environment.

Initialization

Sampling procedure parameters:

batches (M), batch size (N), stopping conditions.

DE algorithm parameters:

population size, mutation rate, crossover rate, max number of generations, and stopping rules.

Begin

Generate an initial population;

$\eta = 0$

While (stopping conditions of sampling procedure are false) do

$\eta = \eta + 1$

 For η scenarios // Parallel computing: assign η discrete MIP problems to available computer processors

 While (termination conditions of DE are false) do // execute each MIP problem

 For solution vector = 1 to population size

 Crossover;

 Mutation;

 Infeasible solutions repair mechanism;

 Evaluation;

 End For (population size)

 End While (termination condition of DE)

 End For (η scenarios)

End While (stopping conditions of sampling procedure)

Figure 4. PSDE procedure.

5. Experiment and discussions

5.1. Illustration

A firm is assumed to use technology 1 to produce 10 product types over an 8-period planning horizon under an MTO strategy, given the products' short life cycles. Nine new technologies are assumed to be potentially available to replace the current technology. These technologies are introduced sequentially with specific probabilities and provide the same functionality as the current technology while offering higher productivity and unit profit but require higher investment costs and yield higher salvage values. The numerical experiment is implemented in MATLAB and conducted on a computer equipped with an Intel Core i7-3770 CPU (3.4 GHz, 8 cores) and 128 GB of RAM. The input data and parameter settings are provided in Appendix A.

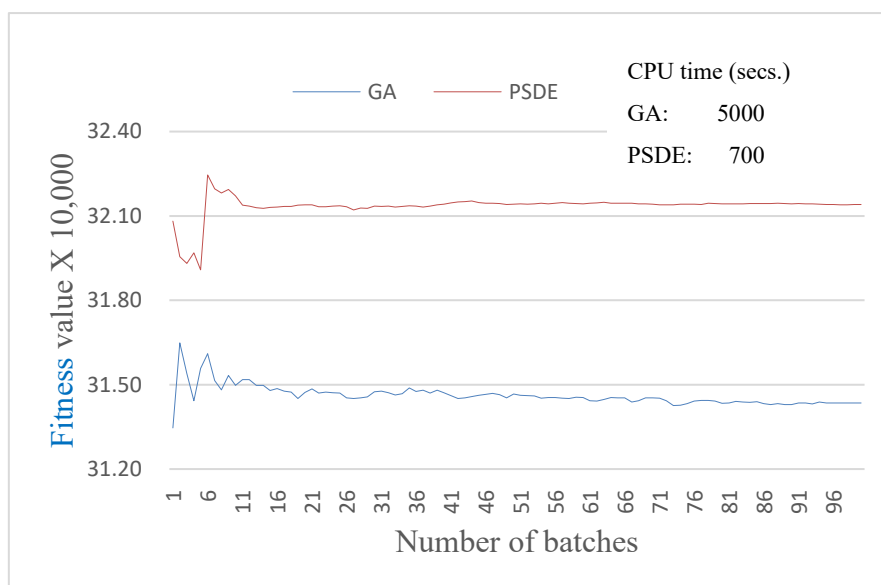
For the rest of this paper, in Section 5.2, we evaluate the computational performance of PSDE, in Section 5.3, we examine the effects of demand and technology uncertainties on expected profit, in Section 5.4, we investigate their impacts on technology adoption policy, and in Section 5.5, we present the solution for the numerical example.

5.2. Performance of PSDE

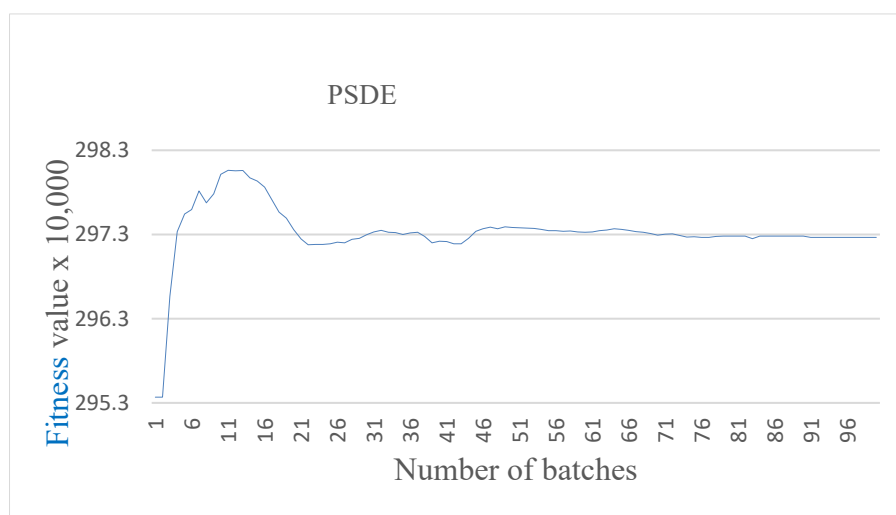
PSDE is employed to solve the stochastic capacity planning and resource allocation sub-problem associated with each action n in the proposed SDP model. We employ Eq. (3) as an objective, which is constrained by Eqs. (4–9). The sub-problem consists of 10 product types over an 8-period planning horizon. Under the SAA scheme, the demand for each product is assumed to be *i.i.d.* and normally distributed. The sampling procedure terminates when either the maximum number of batches reaches 100, with a maximum batch size of 100 scenarios per batch, or the validation gap falls below 4,000.

To evaluate the computational efficiency of the proposed PSDE, its performance is compared with that of a benchmark GA implemented in MATLAB [49]. Both methods are population-based evolutionary algorithms, but they employ different evolutionary operators. For PSDE, the DE algorithm is configured with a population size of 100, a mutation factor of 0.1, and a crossover rate of 0.6. These parameter settings are adopted based on the recommendations of Price et al. [48]. The benchmark GA is implemented using the default settings. This comparison serves as an implementation-level check of computational efficiency rather than a general claim of algorithmic superiority.

As shown in Figure 5, PSDE achieves better computational efficiency than the benchmark GA. PSDE completes 100 batches of demand realizations in 700 seconds, substantially reducing the computational time compared with the GA solver while achieving a higher profit. Furthermore, PSDE maintains its computational efficiency as the problem size increases, demonstrating its scalability for larger-scale problems (Figure 5b).



(a) Fitness Evolution of GA and PSDE (10 product types, 8 periods)



(b) Fitness Evolution of PSDE: a large-scale problem (30 product types, 24 periods)

Figure 5. Fitness value evolution (maximum number of batches = 100, $\lambda = 0.5$).

5.3. Impact of demand uncertainty on expected profit

In this section, we present a set of what-if analyses to examine how demand uncertainty affects expected profit. The SAA scheme, PSDE settings, and problem size remain consistent with those described in Section 5.2. Figure 6 reports the expected profit under different demand distributions and levels of demand variability. The results show that higher demand variability generally reduces expected profit under Normal and Uniform demand distributions. This suggests that the dispersion of demand, in addition to its expected level, is an important factor affecting the profitability of capacity planning and resource allocation decisions.

The results also indicate differences between the Normal and Uniform scenarios, suggesting that the profitability of the resulting capacity plan may depend not only on the magnitude of demand

variability but also on the underlying demand distribution. From a managerial perspective, greater demand uncertainty can increase the risk of capacity mismatch and reduce the predictability of returns from capacity and resource investments. This finding is particularly relevant to technology adoption decisions, as investments in new technology should be evaluated jointly with the uncertainty surrounding future demand.

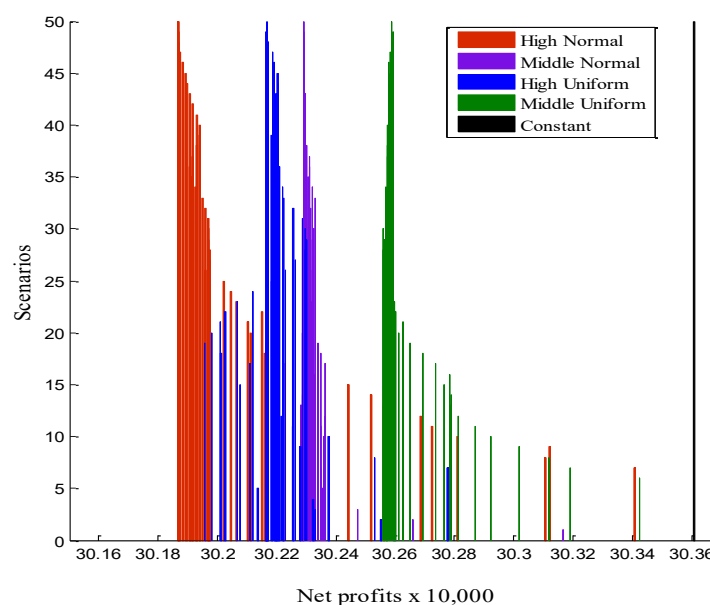


Figure 6. Profits of scenarios ($\lambda = 0.5$) under different demand distributions (Normal vs. Uniform) and demand variability ($\sigma = 20\%$ and $\sigma = 10\%$ of average demand are considered as high variability and average variability, respectively).

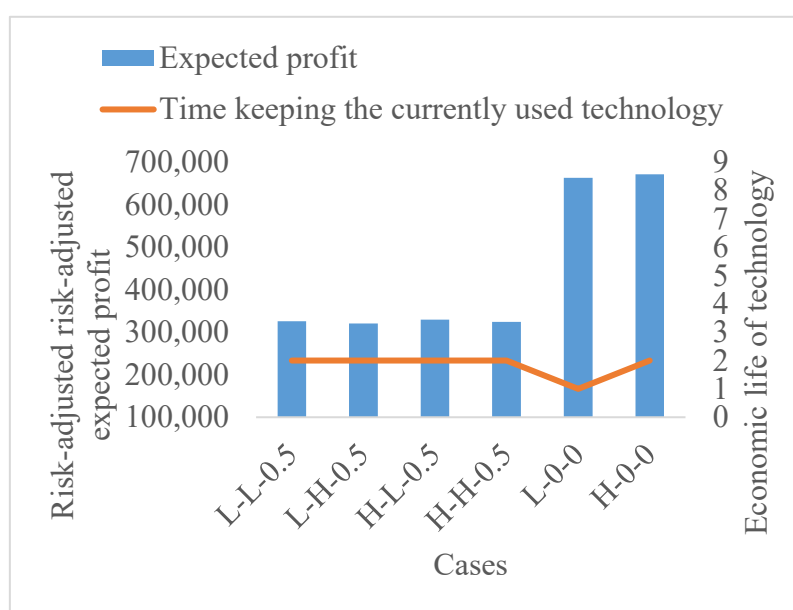
5.4. Impact of demand and technology uncertainties and risk attitude on technology adoption policy

In this section, we examine how long the current technology should be retained when the arrival of new technologies and future demand are uncertain, and how the answer depends on the decision maker's attitude toward profit dispersion. Three factors are varied, as specified in Appendix B: the probability of new technology introduction (low, L; high, H), demand variability (zero, 0; average, L; high, H), and the risk factor λ . The four combinations with demand uncertainty are solved for $\lambda = 0, 0.3, 0.5$, and 0.7 , and the two deterministic benchmarks for $\lambda = 0$, since the MAD is then zero; this gives 18 cases. Since PSDE maximizes the scenario profit of Eq. (9) and λ enters only Eq. (3), the sub-problem solutions do not depend on λ , and the SDP is also solved for $\lambda = 0, 0.01, \dots, 1$. The firm holds 20 machines of technology 1 at $t = 0$. The problem size and the PSDE procedure are those in Section 5.2.

As shown in Figure 7, with $\lambda = 0.5$, the current technology is retained for two periods in all four cases with demand uncertainty, after which the decision is re-evaluated in the technology state reached; in the deterministic benchmarks, the economic life is one or two periods. The value of the policy is flat around the optimum: in all six cases, the second-best action is at most 0.45% worse than the optimal one. The two uncertainties mainly affect the expected profit. A high probability of new technology introduction raises the risk-adjusted expected profit, because more profitable technologies become available earlier. Higher demand variability lowers it at each step, from zero to average and from

average to high variability, consistent with Section 5.3, but does not change the economic life at $\lambda = 0.5$. The effect of the two uncertainties on the timing of adoption therefore arises through the risk attitude, as analyzed below.

Figure 8 and Table 1 show how the risk factor affects the economic life of the current technology at $t = 0$. Below a threshold λ^* , the economic life is two periods, as for the risk-neutral policy (three periods for $\lambda = 0.82$ to 0.84 in case H-L); from λ^* on, the current technology is retained until the end of the planning horizon.



Note: a case = (Probability of new technology introduction-Demand variability level-Risk of investment (λ)), where L=Low, H=High.

Figure 7. Impact of technological innovation speed, demand variability levels, and risk of investment on the expected profits and economic life of the current technology.

For a fixed policy, the objective value equals $(1 - \lambda)$ times its expected profit minus λ times its accumulated MAD, where both are expected discounted sums, over the technology path, of the mean profit and the MAD of the actions taken. Retaining the current technology, which lowers the expected profit and the accumulated MAD, is therefore preferred to the risk-neutral policy when $\lambda/(1 - \lambda)$ exceeds the expected profit forgone per unit of MAD reduction, that is, when λ exceeds the implied threshold in Table 1. It lowers the accumulated MAD because the MAD is charged per action and profit deviations partly offset each other within one action. High demand variability more than doubles the MAD reduction, whereas a high probability of new technology introduction more than doubles the expected profit forgone, since retaining the current technology then forgoes more profitable technologies (Table 1). Hence, the expected profit forgone per unit of MAD reduction ranges from 1.0 (L-H) to 4.9 (H-L), and λ^* ranges from 0.51 to 0.85; it is lower under high demand variability and under a low probability of new technology introduction. The observed λ^* lies slightly above the implied threshold because the policy below λ^* also adapts its later actions.

For a given economic life, λ does not change the capacity plan; the long economic life is supported by more owned and less rented capacity, since purchased machines are paid for once per economic life and rented machines in every period. Three caveats apply: The accumulated MAD captures the

demand-driven profit dispersion within each action, whereas the uncertainty of the technology path enters Eq. (1) through its expectation; λ^* is estimated from SAA rewards, so only the differences between cases are interpreted; and since capacity is optimized for each demand realization, the estimated profit is an upper bound on the profit attainable when capacity is committed before demand is observed, so the effect of demand variability is likely to be understated.

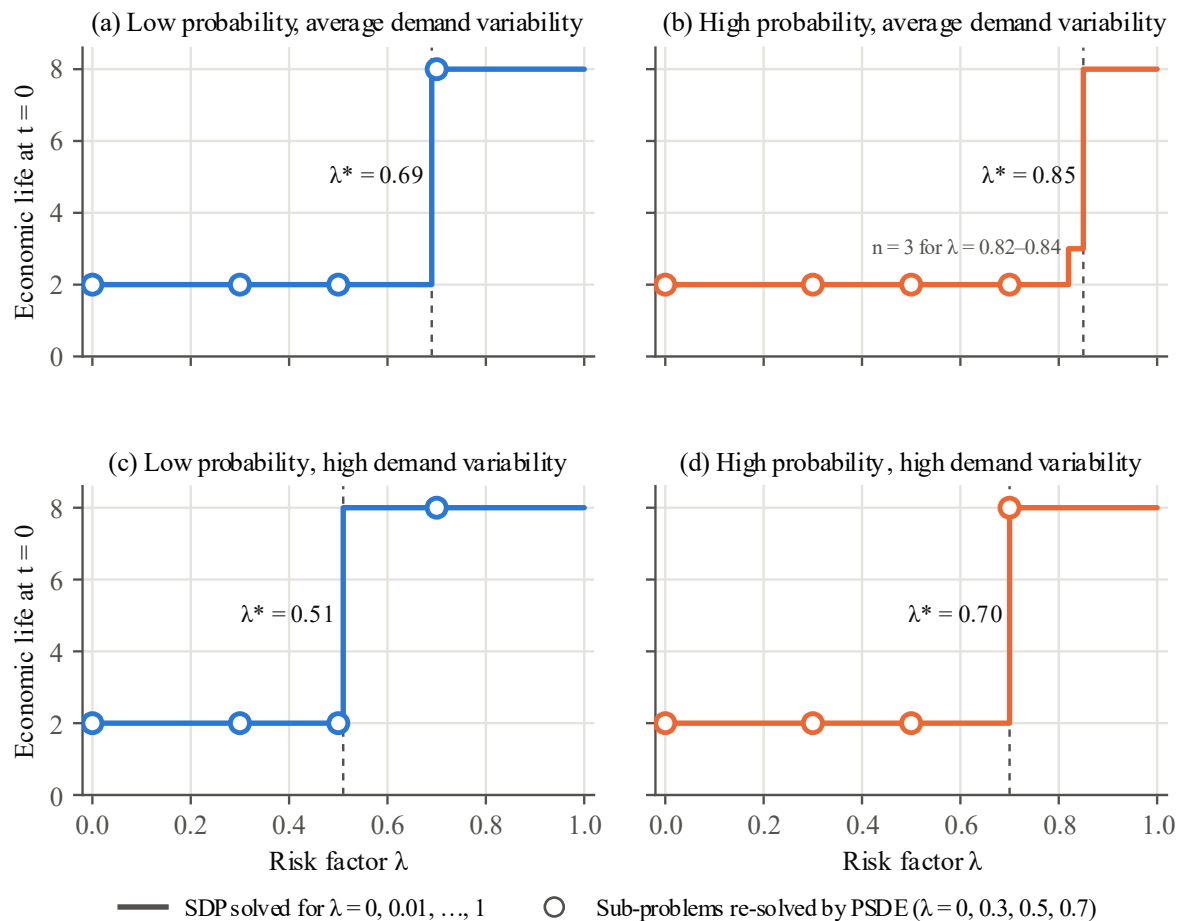


Figure 8. Economic life of the current technology at $t = 0$ as a function of the risk factor λ . (λ^* is the smallest value of λ at which the current technology is retained until the end of the planning horizon).

The findings of this section can be summarized as follows.

(1) A short economic life followed by re-evaluation is optimal at the reference risk attitude: The current technology is retained for one or two periods in all six cases of Figure 7.

(2) Technological and demand uncertainties mainly affect profitability. A high probability of new technology introduction raises the expected profit, and higher demand variability lowers it at each step, but neither changes the economic life at $\lambda = 0.5$.

(3) The risk attitude determines whether the current technology is retained until the end of the planning horizon. This occurs when λ reaches a threshold λ^* between 0.51 and 0.85, at which retaining the current technology reduces the accumulated MAD by 26% to 34% at a cost of 0.8% to 2.1% of the expected profit. The threshold is lower under high demand variability and under a low probability of

new technology introduction, so these two uncertainties affect the timing of adoption only for a sufficiently risk-averse decision maker. A decision maker can therefore decide whether to retain the current technology by comparing $\lambda/(1 - \lambda)$, which measures the expected profit the decision maker is willing to forgo per unit of MAD reduction, with the corresponding value in Table 1.

(4) The risk attitude affects the capacity plan only through the economic life: For a given economic life, λ does not change the capacity plan, and a long economic life is supported by more owned and less rented capacity.

Table 1. Trade-off between the risk-neutral policy ($\lambda = 0$) and retaining the current technology until the end of the planning horizon.

Case	Reduction in expected profit	Reduction in accumulated MAD	Expected profit forgone per unit of MAD reduction	Implied threshold of λ	Observed threshold λ^*
L-L	5,151 (0.78%)	2,496 (25.9%)	2.06	0.67	0.69
H-L	13,094 (1.96%)	2,690 (27.3%)	4.87	0.83	0.85 ^a
L-H	5,960 (0.90%)	5,900 (31.8%)	1.01	0.50	0.51
H-H	13,943 (2.09%)	6,487 (33.8%)	2.15	0.68	0.70

*Note: *Reductions relative to the risk-neutral policy (percentages in brackets); SAA estimates. Implied threshold: the value of λ at which $\lambda/(1 - \lambda)$ equals the expected profit forgone per unit of MAD reduction; above it, retaining the current technology is preferred to the risk-neutral policy. Economic life at $t = 0$: two periods below λ^* , eight periods from λ^* .

^aThree periods for $\lambda = 0.82$ to 0.84 .

5.5. Illustration case

Table 2–4 shows the suggested solution for the base case of Appendix A ($\lambda = 0.5$), in which the firm holds 20 machines of technology 1 at $t = 0$. The optimal action at $t = 0$ is to retain the current technology for one period and then re-evaluate the decision (Table 2); retaining it for two periods. At $t = 1$, the decision depends on the technology available (Table 4). Moreover, if no new technology has been introduced, which occurs with probability 0.3, the current technology is retained until the end of the planning horizon; if technology 2 or 3 is introduced, it is adopted and the decision is re-evaluated after one period; and if a more advanced technology (4 to 7) is introduced, it is adopted and retained until the end of the horizon. Table 2 and 3 report the capacity and production plan of the first period. Since this plan is optimized for each demand scenario, the table shows the plan of one demand scenario: The firm rents 23 machines in addition to the 20 machines on hand and purchases none, because renting a machine for one period costs less than purchasing it and selling it at its salvage value.

Table 2. The suggested solution for one demand scenario.

Period (<i>t</i>)	0	1
<i>Technology adoption policy</i>		
Technology type	1	1
<i>Resource portfolio</i>		
At initial period ⁽¹⁾	20	
Purchased ⁽²⁾		0
Rented ⁽³⁾		23
Net=(1)+(2)+(3)		43

Table 3. The suggested production quantity plan.

Product type	Period (<i>t</i>)
	1
1	51,588
2	44,351
3	57,044
4	59,655
5	61,734
6	46,008
7	51,484
8	56,387
9	71,199
10	57,399

Table 4. The suggested decision at the next decision epoch ($t = 1$).

Technology available at $t = 1$	1 ⁽¹⁾	2	3	4	5	6	7
Probability	0.3	0.2	0.1	0.1	0.1	0.1	0.1
Technology type adopted	1	2	3	4	5	6	7
Periods retained	7 ⁽²⁾	1	1	7	7	7	7

*Note: ⁽¹⁾ No new technology introduced. ⁽²⁾ Until the end of the planning horizon. Expected profit of the policy 660,985; accumulated MAD 9,721; objective value 325,632.

6. Conclusions

In this study, we developed an integrated stochastic framework that jointly addresses technology adoption, capacity planning, and resource allocation under technological and demand uncertainties. The framework combines an EL model for technology adoption with an SMIP model for operational capacity planning and resource allocation. It also captures several practical features of technology-intensive manufacturing, including the time value of capital, the cost of unmet demand, alternative machine investment options, salvage value and the decision maker's attitude toward profit dispersion.

To efficiently solve SMIP problems, a PSDE framework with an infeasible-solution repair mechanism was proposed.

The numerical results provide four main findings. First, PSDE achieves better computational efficiency than the benchmark GA while maintaining competitive solution quality, and its performance remains effective as the problem size increases. Second, technological and demand uncertainties mainly affect profitability: A higher probability of new technology introduction raises the expected profit, whereas greater demand variability lowers it. Third, the optimal policy retains the current technology for a short period and then re-evaluates the decision, and this result is robust because the value of the policy is flat around the optimum. Fourth, the current technology is retained until the end of the planning horizon only when the decision maker's risk aversion exceeds a threshold, which is lower under high demand variability and under a low probability of new technology introduction; the longer economic life is then supported by more owned and less rented capacity. These findings demonstrate that technology adoption decisions should not be made independently of operational capacity, demand conditions, and the decision maker's risk attitude.

Several limitations provide directions for future research. The current model assumes i.i.d. demand and sequential technological evolution following a Markov process. Since capacity is optimized for each demand realization, the estimated expected profit is an upper bound on the profit attainable when capacity is committed before demand is observed; a two-stage formulation in which machine purchases are decided before demand is realized is a direction for future research. Moreover, the numerical study is based on illustrative instances, and a validation with industrial data would further strengthen the findings. In future studies, researchers could consider correlated and non-stationary demand, more flexible technology-transition processes, such as competing technologies that coexist and substitute for one another, a decline in unit profit that depends on the adoption rate of new technologies, and empirical data from industrial applications. The framework focuses on a single-firm setting; researchers could incorporate inter-firm resource sharing to better represent collaborative capacity and resource planning. In addition, the number of SMIP sub-problems grows as $O(IT^2)$, so the computational burden becomes substantial for long planning horizons combined with large sub-problems, even with parallel computing. Researchers could reduce this burden through approximation or aggregation strategies.

Finally, although we focus on a high-tech manufacturing setting, the proposed framework can be extended to other technology-intensive industries, such as semiconductor testing, display manufacturing, electronics, battery and energy storage manufacturing, and other advanced manufacturing systems. These industries share important characteristics with the setting considered here, including rapid technological evolution, stochastic demand, capital-intensive equipment, and significant technology replacement costs. By adapting the technology-transition, demand, capacity, and investment parameters to specific industry contexts, the framework can provide a useful basis for evaluating technology adoption and capacity investment decisions under uncertainty.

Author contributions

Kung-Jeng Wang and Hong-Phuc Nguyen proposed the methodology; Hong-Phuc Nguyen wrote the original draft; Kung-Jeng Wang reviewed and edited the manuscript. All authors have read and agreed to the published version of the manuscript.

Use of Generative-AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

The authors declare that there is no conflict of interest.

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